

A COMPREHENSIVE REVIEW ON ARTIFICIAL INTELLIGENCE BASED MACHINE LEARNING TECHNIQUES FOR DESIGNING INTERACTIVE CHARACTERS

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ABSTRACT

The recent progress in artificial intelligence based machine learning techniques has renewed interest in building and designing the interactive characters. To achieve optimal performance many techniques have been used along with the neural networks, which are prepared end to end in tasks such as object recognition video games and board games. In this paper, a review of current literature is carried out where the challenges in real time strategy game and the tasks in a real-time environment are explored. The comparative analysis is made on different AI based machine learning techniques to comprehend the performance issues and other challenges faced. Furthermore, discussion of the advantages and disadvantages of each technique is conducted so as to understand and compare the efficiencies with the existing techniques based on the strategies.

KEYWORDS: Artificial Intelligence, Machine Learning, Real Time Strategy

Received: Apr 16, 2018; **Accepted:** May 07, 2018; **Published:** June 01, 2018; **Paper Id.:** IJMCARJUN20181

INTRODUCTION

Artificial intelligence is one of the most sorted techniques used in the background of a game and is considered as major factors for fun and other factors in commercial computer games. Understanding and developing intelligent systems which have all the traits of human is the aim of artificial intelligence. The artificial intelligence is getting smarter day by day in virtual worlds. The earliest use of the artificial intelligence in games was in 1952, and it was created by a graduate student in the UK which helps in playing a perfect game of tic-tac-toe. At present, a team of researchers is working on and has succeeded in creating AI's that helps in defeating humans in more complex games. By developing the human language in children the development of the action, conceptualization and social interaction helps in providing mutual help. Language requires bringing together of many different processes and draws attention to the need for an interdisciplinary approach (Llobera et al., 2017). So, the work in developmental robotics, cognitive science, psychology, linguistics, neuroscience, engineering is included.

Data-driven motion synthesis allows animators to produce convincing character movements with high-level parameters. The various techniques that make use of large motion capture datasets and machine learning to parameterize motion have been proposed in computer animation. The artificial intelligence data approaches needs

major amount of data preprocessing which also includes motion segmentation, alignment and labelling. So preprocessing is carefully performed by the human intervention and the results obtained appear smooth and natural by making full automation difficult and thereby require technical developers to maintain. Continuous based motion mechanism is required for the interactive character control and the motion graphs are effective for such purpose (Arikan and Forsyth 2002; Lee et al. 2002; Kovar et al. 2002). To enhance the data set the motion graphs replay captured motion data and techniques are used in the same class (Min and Chai. 2012). The motions in the graphs need to be classified, segmented and aligned by applying motion blending for motion synthesis during interactive character. Even though (Kovar and Gleicher. 2004) try to execute the process the choice of the distance metric between motions and segmentation in motion sequence which directly affects the performance and accuracy. Furthermore, the framework mixes all motions present nearby for incorporating realistic movements without any motion segmentation and classification. Techniques based on the reinforcement learning are used at each step following the user instruction. (Safonova and Hodgins. 2007). Precomputation is performed in reinforcement learning which increases exponentially concerning the number of actions available to the character. Levine et al., (2012) reduced the dimensionality by dividing the motion dataset into different classes. The reinforcement learning is avoided and avoids the high level commands provided by the user to the low-level motion features and thus the mapping is resolved by a number of parameters in reinforcement learning.

CHALLENGES IN REAL TIME STRATEGY GAME

The military unit as an application used in real-time strategy games. This type of game contains screen which has mapped area and contains buildings, units and terrain. Usually, several players are present in an RTS game. Other than the players there are various game entities called participants, units and structures. In recent years, it is shown that these games pose a challenge to artificial intelligence (Sethy et al., 2015). The design of the artificial intelligence players for these games which are capable of beating average human players are challenging because,

- RTS games usually control the large number of units which can be controlled simultaneously.
- RTS games are real time.
- Real strategy games involve attributes such as observability, actions which further depict instructions on the AI techniques which is later deployed.

RTS games own a variety of military units used by the players to wage war and uses units and structures to aid in resource collection, unit production. According to the game while playing the match players must balance the development of the economy, infrastructure associated with the military units. They also contain the available units to easily attack and defend in the present and more resources and upgrades to win later. Thereby they also decide which units and structures to produce and the technologies to be used all through the game to capture the appropriate composition of groups at the correct times to have access to the proper balance of groups at the appropriate times. Recent RTS games have stimulated the creation of new units with new concepts and architectures and led to increased number of publications addressing open AI problems in RTS games. These types of games have long term goals and needs greater levels of abstraction and reasoning. Further, it contains a vast space of actions and game states with actions which has long term effects throughout. Considering the theoretical point of view, the differences between the RTS games and traditional games such as chess are;

- Players can issue actions at the same time (simultaneous moves), and most actions take some amount of time to complete (durative actions). While, in Chess, moves alternate between players and the actions are instantaneous.

- RTS games are real-time, which means players do not need to wait for their opponents to go to the next move, for example, StarCraft is updated at 24 iterations per second, hence players can issue a new move every 42 ms. Considering in Chess, players may have several minutes to decide the next move.
- Most RTS games are partially observable due the fog-of-war that only lets observe the area of the map under the sight range of the player's units, while games like Chess are perfect information games.
- Most RTS games are non-deterministic, since some actions might have a chance of failure, and some other actions might have multiple possible outcomes.

Synnaeve and Bessiere (2016) tackle the problems of having partial information and the inherent computational complexity of RTS games. So proposed a Bayesian modelling framework that can handle the game at three interconnected levels of abstraction doing inference at each level.

Chung, Buro, and Schaeffer (2005) created a capture the flag game which depicts that the player is needed to control the group of units to direct through the obstacles to the other side of the map and retrieve the opponent's flag. Later a generalized Monte Carlo planning framework and then applied it to the game, giving positive results.

The challenges that are faced by the real time gaming systems are briefed below,

Adversarial Real-Time Planning

Domains in which agents compete against one another are termed adversarial (Willmott et al., 2001). As it is well known that the real time strategy games and its actions are performed in real time, so that the players take decisions under major restriction and executes continuously. Turn based game agents considers the environments, but the fact is that the game is not happening in real time which makes challenge difficult to avoid. As the sizes of the state space and the action space are much larger than the existing ones, a game tree search approaches are not directly applicable due to a large game tree to explore. One of the best available solutions is using multiple levels of abstraction and perform an adversarial game tree search in few problems such as long-term planning or short-term planning. As the abstractions are based on a time the temporal reasoning is one of the important elements to be considered. In case of high-level representative, the combat between the models needs to look into as there are large armies (Alberto Uriarte, 2017).

Decision Making Under Uncertainty

Considering most of the RTS games, NPC has all the information regarding the game state such as a location of the player units and buildings. The situation is considered as cheating as the players doesn't have information and to overcome this situation the imposition of the observability in RTS games, making sure that all the players play the game on equal terms. This problem doesn't occur in turn based games as the player has the location information including game states.

Opponent Modeling

The concept is that the players have strength to analyze the ability of the enemies actions and find out the weakness which exploits the future games. So the artificial games needs to be cleared to find the opponent's plans and identify their behaviors on basis of previous observations and the challenge is not an exclusive in RTS games as in any other games modeling the opponent will be useful.

Spatial and Temporal Reasoning

During the game play the maps are used as the components with more popularity. Agents can develop better offensive plans and more organized resources gathering as well. The main advantage of the human players is that they have excellent knowledge in temporal relations of actions.

Resource Management

RTS games develop new technologies and also new resources which are used to upgrade buildings and units. The resources or the attributes present is spread throughout the map and further it is combined obtained for buildings placed in certain places on the map. Therefore, for the successful strategy the proper resource management strategy is considered.

Collaboration

During an RTS game, each player generates many units and thus these units are considered as a multi agent system and thus it is important to develop coordination methods that lead to a good team tactics and strategies. There is not only a collaboration at unit level, but also team matches which have two or more team players.

Pathfinding and Content Generation

Finding out the suitable paths in an easy manner between the two locations in a map is considered as one of the important tasks in RTS games. Many moving objects are considered while calculating paths as the game environment is dynamic. It also contains more aspects such as keeping unit information, taking terrain properties.

Game content contains all matters of game that affects the game play than playing with the non player character behavior and also the game engine. In RTS games the content is assorted such as maps, units, buildings (Cabrera et al., 2013)

CHALLENGES IN BUILDING HUMAN LIKE MACHINES

The toughest task for machine learning and artificial intelligence is learning simple video concepts (Lake et al., 2015).

The Characters Challenge

The handwritten character recognition, which is one of the main challenges which becomes a problem for comparing different types of machine learning algorithms. In this, handwritten character recognition is a major problem and this also simpler than more general forms of object recognition. People are great learners than the algorithms for concern regards character recognition. People try learning more and attaining the human level learning abilities in machines which are called as character challenge. People can efficiently integrate across multiple examples of a character to infer which have optional elements. The progress continues by combining the deep learning and probabilistic program induction to tackle the higher versions of character challenge.

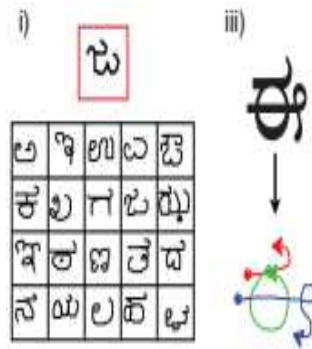


Figure 1: The Character Challenge: Human Level Learning of Handwritten Characters

The Frostbite Challenge

The second challenge concerns the Atari game frostbite, which was considered as one of the control problems (Minh et al., 2015). In this, the network is trained to play 49 classic Atari games proposed as test domain for the reinforcement learning (Bellemare et al., 2013). In frostbite, players control an agent tasked with constructing an igloo within the time limit. The igloo is built piece by piece as the agent jumps on ice. The challenge is that the ice floes are in stagnant motion and only the ice floes contribute to the construction of the igloo. The agent may also earn extra points by gathering fish in the water and thereby avoiding major hazards.

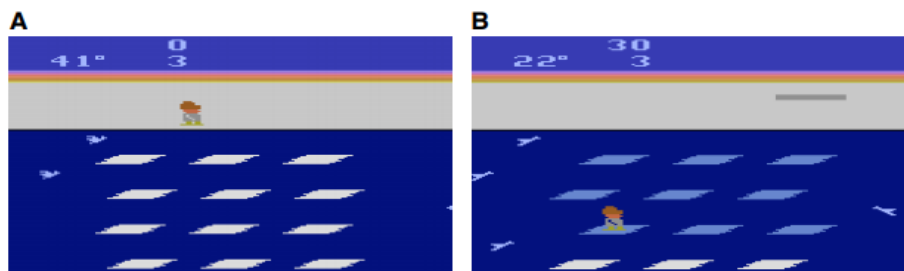


Figure 2: Screenshots of Frostbite, a Video Game Designed for Atari Game Console

TASKS IN REAL TIME ENVIRONMENT

Because of the characteristics, RTS games have many challenges to deal. The below shows the problems to be faced in real-time environment:

Planning

Humans consider few actions to form the strategy and that is considered as plan. Planning is considered as the process of determining the action sequences which accomplishes a goal when the task is executed. The planning process becomes quite difficult because of the presence of contender in addition to real time and hidden information. Aha et al., (2013) proposed a plan retrieval algorithm where three key sources of domain knowledge are used along with the removal of the assumption of a static component. . Moore et al., (2008) introduced an integrated algorithm called RL/CBR which uses continuous models instead of discrete approximation. The algorithm is named as continuous action and state space learner (CASSL). Alcazar et al., (2008) PDDL was used to define a planning domain that is used to implement an artificial player based on automated planning in a RTS game.

Plan Recognition and Predictions

The process of an agent observing the actions of the other agent, whether it is human or computer based is called as plan recognition.. There are several types of plan recognition, one among them is case-based plan recognition which collects the data on the building construction and is utilized for analysis and divide the players' strategies and style. The probabilistic models of opponent behavior and actions were learned from the sets of saved games. Plan recognition can be categorized into two levels, such as strategic and tactical. Strategic plans dictate the kind of units the player executes and the tactical plans dictate the units deployed.

HUMAN-MACHINE INTERFACE

The neural network modeling is performed and the approaches required for the human intelligence is explained and are as follows,

Development Start-Up Software

Humans have a foundational understanding of several core domains (Spelke and kinzler, 2007). The domains consist of number, space, physics and psychology. The core domains cleave cognition at its conceptual joints and the particular domain is organized by a set of entities and principles relating the entities. Each core domain has become the target of a great deal of study and analysis. All of the domains are important for the machine learning.

Intuitive Physics

The promising recent approach sees intuitive physical reasoning as similar to inference over a physics software engine (Bates et al., 2015). According to the hypothesis, people reconstruct the scene using representations of the objects and few properties and also the forces acting on objects. The intuitive physics engine approach enables flexible adaptation. It is quite difficult to integrate object and physics-based primitives into deep neural networks.

Intuitive Psychology

Intuitive psychology is another early emerging ability which is influenced by human learning and thought. Animate agents were separated from inanimate objects. The full formal account of intuitive psychological reasoning needs to include representations of agency, goals, and efficiency and reciprocal relations. There are several ways to incorporate the intuitive psychology into contemporary deep learning systems. These abilities are early emerging and play an important role in human learning and thought.

MACHINE LEARNING TECHNIQUES

A system will learn from an experience when it improves in completing a determined task by optimizing its performance. It is also applied in the optimization of the Non-player characters Different machine learning tools and techniques used by different authors are as follows;

Naive Bayes Classifier

This type of machine learning is based on the Bayes theorem. This is a type of learning and prediction technique based on storing a series of attribute-class. The attributes present in the class are independent from each other (Millington et al., 2009). The reviewing of the technique is made on the characteristics in the methods. They are as follows,

- AI flagship
- AI usage
- Categorization of games
- Sample participants
- Publication type

Artificial Neural Networks

These neural networks constitute of a paradigm of learning. These are composed a set of neurons or states and is defined by a set of features. The systems receive a group of inputs and generate a specific output. These ANNs emulate the human brain behavior and is formed by nodes which is connected together to form a network. The ANN gets information from the neighboring neurons and gives an output depending on its weights and functions.

Tan et al., (2013) found the cons of spectrum lack and inefficient in the communication networks and the by introducing new solutions using ANN by replacing the current frequency allocation system.

Yang et al., (2103) introduced genetic algorithms for the design of the cognitive engine and in addition the radial basis function network is used to adjust the parameters of the system to adapt for the environmental changes.

Support Vector Machines

Support vector machines are set of supervised algorithms focused on data analysis and pattern recognition. Data is clustered using hyper planes in a multidimensional space that helps in maximizing the separation between classes. This clustering is dependent on decision boundaries.

These are used for learning models and also as regression analysis. The basic idea behind the SVM is detecting the soft boundary of a given set of samples so as to classify new points. SVM s delivers a unique solution and produce the efficient classifiers with high prediction accuracy. As SVMs are inseparable the input features are mapped into high dimensional feature space (Abbas et al., 2015). Dandan et al., (2011) found that SVM can be used for spectrum sensing and real time detection.. SVM provides high performance in minor problems, but the complexity increases in large problems. SVMs are considered as computationally expensive.

Genetic Algorithms

The genetic algorithms are originated by mutating small FORTRAN programs. Genetic algorithms, search in space with the aim of finding an element that helps in maximizing the fitness function by evolving the population of chromosomes.

Chen et al., (2010) toof genetic algorithms by enhancing the system performance thus by solving the multi objective problems which help in reducing the error rate and power.

Hauris et al., (2007) proposed genetic algorithm for RF parameter optimization in CRR. The genes used are modulation and coding schemes, antenna parameters, transmit and receive antenna gains.

COMPARATIVE ANALYSIS

Table 1

Sl No	Title	Technique Used	Outcome	Research Gap
1.	Review of the Use of AI Techniques in Serious Games: Decision-Making and Machine Learning	Naive Bayes classifier	Non-deterministic.	It requires large number of data records
2.	Review of the Use of AI Techniques in Serious Games: Decision-Making and Machine Learning	Artificial neural networks	Adaptation ability to new changes and complexity is reduced.	Poor generalization and requires training data labels
3.	Recent advances on artificial intelligence and learning techniques in cognitive radio networks	Support vector machines	Generalization ability and the robustness against noise.	Complex with the large problems
4.	Recent advances on artificial intelligence and learning techniques in cognitive radio networks	Genetic algorithms	Multi-objective optimization	High complexity with the large problems and also require prior knowledge of the system.

CONCLUSIONS

This paper presents a review of the artificial intelligence based machine learning techniques for designing interactive characters. The table above gives the comparison techniques discussed in the review. The machine learning techniques used are naive Bayes classifier, support vector machines, genetic algorithms and neural networks. The techniques used to create a new intelligent, serious game and to provide the players with a real experience. Further comparing the techniques it is observed each technique has its own pros and cons whereas neural networks are better compared to other techniques and thus help in designing of the player characters in video games. Also, future work is to extend the state of the art in the field of games by creating a knowledge hub and also to address more AI techniques.

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